Advanced Sensing, Degradation Detection, Diagnostic and Prognostic Capabilities for Structural Health Management

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ABSTRACT

Analatom is developing a Structural Health Monitoring (SHM) system which provides both corrosion and strain measurements. This combination of data provides critical assessment of structural health, leading to prediction of failure. The SHM system's sensors can be permanently installed in high value structures, such as buildings, bridges, or aircraft, and are connected to data acquisition nodes where initial processing is performed. From the nodes, processed data is transmitted using a ZigBee/IEEE 802.15.4 compliant low-power, self-organizing, self-healing wireless network to a central PC hub for analysis and interpretation. Analatom's μLPR corrosion sensors have been installed on a mock-up bridge cable at Columbia University as part of a large project on development of a corrosion monitoring system for main cables of suspension bridges. The sensors were placed inside a full-scale mock-up suspension bridge cable located in an environmentally controlled chamber subjected to accelerated corrosion conditions for one year. The μLPR sensors recorded corrosion rate measurement at 8 different locations inside the cable showing excellent agreement with temperature measurements.

INTRODUCTION

Recent studies have exposed the generally poor state of our nation's critical infrastructure systems that has resulted from wear and tear under excessive operational loads and environmental conditions. SHM (Structural Health Monitoring) Systems aimed at reducing the cost of maintaining high value structures by moving from SBM (Scheduled Based Maintenance) to CBM (Condition Based Maintenance) schemes are being developed. These systems must be low-cost, simple to install with a user interface designed to be easy to operate. To accomplish these three points the system combines arrays of sensors connected to a data acquisition processor with wireless communication nodes that transmit data to a central processing server which uses Artificial Intelligence (AI) algorithms to perform diagnostic and prognostic assessments of the information.

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To reduce the cost of the system and make it simple to install, a generic interface node that uses low-powered wireless communications has been developed. This node can communicate with a myriad of common sensors used in SHM. In this manner a structure such as a bridge or ship can be fitted with sensors in any desired or designated location and format without the need for communications and power lines that are inherently expensive and complex to route. Data from these nodes is transmitted to a central communications Personal Computer (PC) where AI algorithms analyze the data. AI is used as it allows large data streams to be analyzed using non-linear transfer functions and produce a 'simple' output that effectively indicates both abnormal behavior and trends in the structure.

In this paper as an example of a typical system, micro Linear Polarization Resistance (µLPR) corrosion sensor system is demonstrated to monitor corrosion in bridge suspension cables on a mockup cable installed at Columbia University. The system components, operation and installation are given in technical detail.

µLPR CORROSION SENSOR SYSTEM

µLPR Corrosion Sensor

Although well developed and understood the LPR technique has not been widely adopted for SHM (Structural Health Monitoring) as the macro LPR sensors and systems are expensive and highly intrusive. The µLPR is based on the macro system; however, expertise in semiconductor manufacturing is used to micro-machine the macro system. Using photolithography it is possible to manufacture the µLPR sensor from a variety of standard engineering construction materials varying from steels for buildings and bridges through to novel alloys for airframes.

Corrosion monitoring presented in this paper uses the µLPR corrosion sensor. The micro µLPR works on the same principle as the macro LPR sensors and is designed to corrode at the same rate as the structure on which it is placed. The micro sensor is made up of two micro machined electrodes that are interdigitated at 150µm spacing. The corrosion reaction – both oxidation and reduction – produces a corrosion current that can be pre-determined empirically for each sensor type. This I/V (Current/Voltage) form is called a Tafel plot.

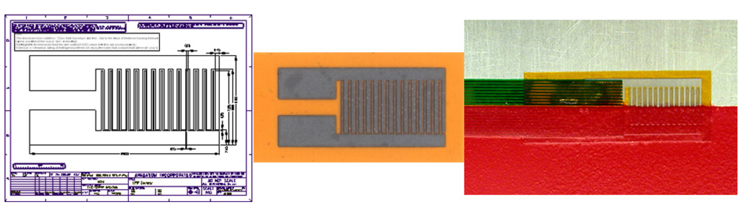

Figure 1: Thin Film µLPR Corrosion Sensor

The µLPR sensor is made from shim stock of the source/sample material that is pressure and thermally bonded to Kapton tape. The shim is prepared using photolithographic techniques and Electro Chemical Etching (ECM). It is further machined on the Kapton to produce a highly ductile and mechanically robust micro sensor that is very sensitive to corrosion. Examples of the sensor schematic, an actual sensor and a fitted sensor are shown below in Figure 1.

Sensor System Electronics

A low current and voltage circuit samples the μLPR sensor in operation. This ensures that no corrosion occurs during measuring the device's I/V characteristics. This circuit gives the effective corrosion resistance of the sensors between interdigitations. Using this resistance and the Tafel constants it is then possible to obtain a direct measurement of the corrosion rate on the structure that is being monitored.

The Data AcQuisition (DAQ) system uses a network of nodes that interface with sensors and transmit the sensor data to 'coordinator' nodes which in turn transfer the data to a PC/data bank. Running on the PC is the SHM software that allows real-time and historical representation of the data/structure being monitored. At the heart of DAQ node is a TI (Texas Instruments) MSP430 MCU (Micro Controller Unit). The MCU has digital and analog input/output capability. Communication to analog sensors uses external instrumentation amplifiers that are calibrated prior to sensor reading by onboard firmware. Separate external analog switches are also used to minimize cross-talk between readings from sensors. The TI MSP430 MCU is used due to its specific design features for low power applications. To fully utilize the low power features of the MCU the firmware uses minimal system features in operation and turns 'off' the MCU whenever the system is idle. An image of the node PCB is shown in Figure 2.

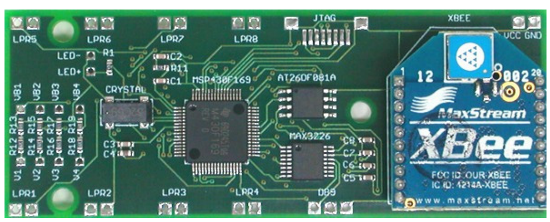

Figure 2: The DAQ PCB has 16 analog input chanels, a digital bus (SPI), ZigBee protocol wireless comunications and USB or RS232 wired comunications.

The DAQ node can handle data rates in excess of 500 total samples per sec (2 bytes per sample). The data does, however, need to be buffered and streamed to the communications module, as such numerous nodes may be required running in parallel to collect multiple sensor measurements of inertial, strain and displacement data due to their higher data rate. Resolution of the on-board Analog to Digital Converter (ADC) is 12 bits. Higher resolution is availed by employing an ADC external to the MCU and modules with this option are available but should not be necessary for this project. Digital input is obtained using the Synchronous Peripheral Interface (SPI) bus available on the MCU. This BUS offers an industry standard in communicating with devices with digitized output. This digital format in conjunction with analog is used for interfacing besides with the μLPR corrosion sensor also with displacement sensors, accelerometers and tilt sensors.

Sensor System Architecture

The system architecture is shown below in Figure 3. Communication between nodes and the coordinator (Master Node) is wireless using the ZigBee protocol. The coordinator communicates to the main hub (PC/data bank) on the

802.11 protocol, although the system can be directly connected using a USB connection. While the system is designed to be self (battery) powered, it should be noted that higher data rates required for displacement, inertial and video capture will deem it necessary to power the high duty cycle nodes from external power. One PC workstation is located on each structure (bridge or ship).

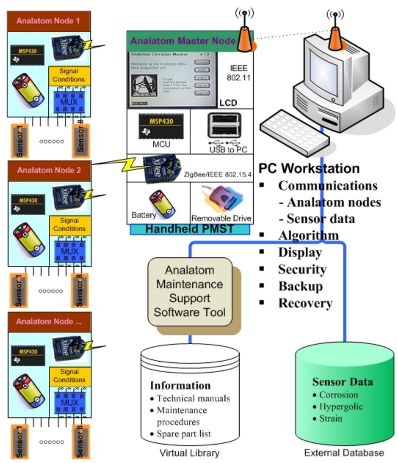

Figure 3: Schematic of the hardware architecure presently employed as part of its SHM system.

The sensor data that resides on the main PC/data bank will be backed up on-site using a raid configuration. Depending on the data volume and the availability of sufficient communications link bandwidth, the system either transmits all collected data to the operator's main server via the internet or at set intervals to data storage units (hard drives) in the data bank. Analysis of the data using 2nd generation neural network technology is performed at the operator's side.

μLPR Corrosion Software

Three levels of software are used for bridge monitoring projects. At the node level is the firmware that is effectively transparent to the end user. The firmware resides in the nodes and handles all sensor interrogation and data transmission. At the next level of operation is the Graphical User Interface (GUI) that configures and visualizes the SHM system operation and sensor data in real time. This software will reside on the local PC data storage module (server). The GUI is configured to suit the specific application. The third and major portion of software employed is the data analysis software. For this, second generation neural network AI is used to deal with the large data pools that the SHM system will generate. Data pools (historically acquired sensor data streams) which have been stored in on-system, passive data bases can now be up-loaded from the onsite, acquisition computer to external (off–site) analysis module servers via (a) satellite, or manually by (b) wireless communication channels on a fixed periodic basis. The up-load to satellite link clearly affords a timelier and more sensitive method of analyzing shifts in sensor signal data feeds. While this choice offers close to real time results, short term periodic (manual) downloads can also support informative predictive assessments since the AI analytical server can accomplish diagnostics on 'all' incoming and acquired data streams in minimal times of just a few minutes.

Data analysis is performed in two parts. Although base-line strain and deflection are set as part of the data retrieval system for individual locations on a structure, the correlation of these data points to one-another are then examined. This forms a multiple-nonlinear vector system and allows for correlation between drift in any bridge section, loading/traffic and other conditions such as weather and seasonal changes. The second part of data analysis employs neural network technology to run anomaly detection. This part of the analysis initially requires visual bridge inspection to correlate anomalies. Data flow is bi-directional, e.g. if the software detects an anomaly, then visual inspection is required and vice-versa. Therefore, if visual inspection detects an anomaly this needs to be reported back to the SHM engineers so that data can be tagged 'anomalous' further enhancing the neural network's learning process. Ultimately the AI system produces a set of nonlinear transfer functions that describe the reaction of the bridge/structure to perturbation and allow for both diagnostics and prognostics on a long-term basis.

Neural Network μLPR Corrosion Data Imaging

Neural networks are very useful for modeling data where the underlying relationships between the data are complex or unknown. Though there is certainly interplay between humidity, pH, strain, and corrosion, it is difficult to develop a model from first principles. This is where a neural network model is useful. A neural network is an adaptable system that can learn complex relationships through repeated presentation of data, and is capable of generalizing to new, previously unseen data. The power and advantage of neural networks lies in their ability to represent both linear and non-linear relationships, and in their ability to learn these relationships directly from the data being modeled. Traditional linear curve-fitting models are inadequate in modeling data that contain complex non-linear relationships.

Figure 4: Steel Plate; Corrosion Damage. **Figure 5**: Digitally Filtered Sensor Data.

Neural network algorithms have been applied to interpolate and represent the areal distribution of corrosion from a μLPR sensor array. Figures 4 and 5 provide an example of applying this technique to a panel placed in a corrosive environment. In this example, the analysis enables a better view of non-uniform corrosion over a metallic panel having one corner submerged in saltwater. Figures 4 and 5 below illustrate an image of the actual corrosion profile for the metal plate exposed to saltwater at the bottom right corner, and the corresponding image calculated from the μLPR sensor data output. Note that the calculated corrosion topography/image based on μLPR sensor data in Figure 5 closely models the steel

plate's actual corrosion densities as shown in Figure 4. Thus with appropriate model development, accurate prediction of the system health status is possible.

μLPR Corrosion Sensor System Bridge Cable Installation

The μLPR sensor location in any cable cross section will allow for corrosion in the cable to be displayed in a number of different formats. For example, cables having a circular center section can have μLPR sensors distributed across the diameter of the cable. The thickness loss reading recorded at each sensor can be interpolated to adjoining sensor, which using the AI algorithms then provides a view of the cross sectional corrosion within the cable. In this manner if, for example, a breach in cable wrapping is present in a specific area, a map can be formed of the cable's corrosion rate similar to that illustrated in Figures 4 and 5.

EXPERIMENTAL PROCEDURE

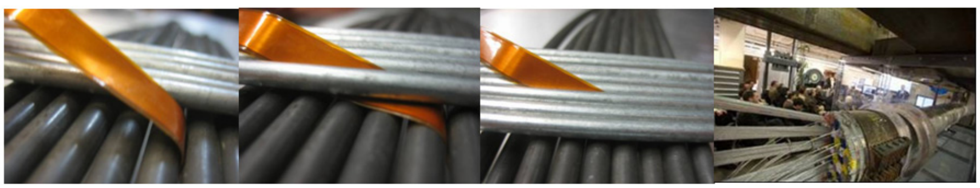

Figure 6: A μLPR Sensor Fitted into the Tight Gaps of a Wrapped Bridge Cable; to Right is the Mock-up Bridge Cable at Columbia University.

It should be noted that the μLPR sensors have been designed to be easily installed within bridge cable windings. The sensors can be fitted on the end of a flexible cable that allows them to be installed into the 'tightest' locations without the need spacers. An example of this is shown in Figure 6 for bridge cables where a μLPR sensor is fitted into the strands of a bridge cable, through the actual strands and out around the tangential wrapping cable. Over time, as the structure begins to deteriorate, the μLPR sensors fitted deep into the structure are able to pick up the onset of corrosion. At this stage in the life of the structure it is far easier to make relatively low-cost changes to the maintenance regime of the structure that has long-term cost saving benefits. In addition, during the life of the structure if events occur that do not fit into the normal behavior of the structure (i.e. an anomaly) the complete SHM system with AI analysis is far more likely to pick this up than scheduled inspection and maintenance, potentially offering significant savings.

The μLPR sensor used in this application is approximately ½ the size of a postage stamp. Thicknesses range from 0.003" to 0.006" making them ideal for installation into hard to access locations such as behind panels, under paint coatings, and inside suspension bridge cables. The sensors can be fitted on the end of a flexible cable that allows them to be installed into the tight locations. A severe environment example of this is shown in Figure 6 for bridge cables.

Here the μLPR sensors are fitted in the interior of a bridge cable, woven between the individual strands. The μLPR sensors were installed on a mock-up bridge cable at Columbia University, shown in Figure 6, as a part of large project, sponsored by FHWA, on the development of a corrosion monitoring system for

main cables of suspension bridges. These sensors were extensively tested in a QFog 1100 Accelerated Corrosion Chamber, before being placed inside a full-scale mock-up of a suspension bridge cable.

The set-up consists of a cable specimen, with a diameter of about 21 in. and with a length of 20 ft, made by 73 127-wire hexagonal strands, for a total of more than 9,000 0.196-in diameter steel wires (Figure 6). The reason for building hexagonal shape strands was to optimize/minimize the void ratio inside the cable and to improve the final compaction of the cable. Of the 73 hexagonal strands, the central 7 ones are 35 ft long and subjected to 1,100 kips tension load while the remaining 66 strands are shorter (20 ft) and unloaded. This unique cable specimen, one of the world's biggest cable specimens ever built in a lab, is placed in a properly designed loading frame so to induce a tensile stress level up to 100 ksi in some of the wires. The idea behind such a high level of stress is to highlight the effects induced by stress-corrosion cracking.

To simulate conditions as close as possible to real operating conditions and to accelerate the corrosion processes in the cable specimen, this cable mock-up was placed inside a large environmental chamber, whose temperature, humidity and aggressiveness of the environment could be properly controlled, and subjected to cyclic accelerated tests. These accelerated tests ran for days, with a typical cycle that consisted of a "rain" phase, of duration ranging from 0.5 to 1 hour, followed by a "heat" phase, lasting from 2 to 4 hours, and by an "air conditioning" phase, that lasted between 2.5 to 3.5 hours. For each test, different pH and NaCl content of the "rain" phase have been considered. These cycles were repeated for days and measurements of temperature, relative humidity and corrosion rate were collected at different intervals. The entire duration of the testing period was over one year.

A total of 72 sensors, including 8 μLPR sensors, were installed in the cross-section of the cable. Sensors were placed along three diameters, inclined at 60^o angle with respect to each other. Such distributions allows us to have measurements that are distributed along the radial direction in order to have a three dimensional distribution of the variations of the various parameters (e.g. temperature, humidity, etc.).

RESULTS

In Figure 7, the measurements of the corrosion rate recorded by 2 μLPR sensors (LPR3 and LPR4) during the test period May 22 – 24, 2009 are presented and correlated with the measurements of the temperature recorded along the vertical diameter of the cable. LPR3 is placed close to the center of the 21 in diameter cable while LPR4 is placed along the radial direction inclined at 60^o at about 6 in from the center.

The temperature measurements show a clear dependence from the position of the sensor relative to the heat source. All the sensors clearly identify 6 cycles: sensor T5, being the closest to the heat source, shows a substantial temperature variation during the cyclic testing while sensor T3 measures an almost constant temperature increase. Sensors T1 and T2, being placed in the bottom half of the cable diameter, measure temperature that are quite similar from those recorded by sensor T3.

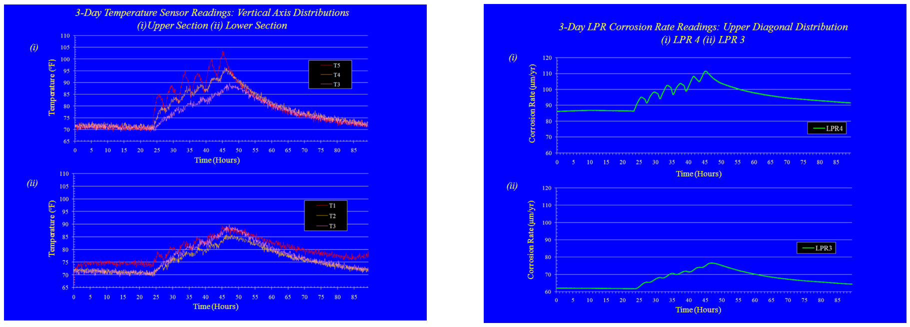

Figure 7: Correlation between Measured Internal Temperature in a Bridge Suspension Cable and μLPR Corrosion Sensor Response.

The 2 μLPR sensors show excellent correlation with the fluctuation of the temperature: being LPR4 closer to external surface of the cable, it records more marked cyclic variations than the one recorded by LPR3. During the ambient condition portion of the test, sensor LPR3 records a constant corrosion rate of 62 μm/yr while, during the cyclic phase, it shows an average corrosion rate of 2.54 μm/yr per cycle. Sensor LPR4 shows instead a constant corrosion rate of 86 μm/yr and an average corrosion rate of 8.08 μm/yr per cycle and an average increase in the minimum corrosion rate of 3.75 μm/yr per cycle. The initial difference of corrosion rate (62 μm/yr versus 86 μm/yr) between the two sensors can be attributed to possible different conditions inside the cable.

CONCLUSIONS

A SHM platform has been described for monitoring corrosion related fatigue and environmental impact on high value structures, such as bridges, aircraft, and buildings. Evaluation of multi-dimensional sensor information correlated to direct corrosion rate measurements provides a powerful tool for diagnostics and prognostics of structural fatigue and remaining life estimates for critical structures. An example of μLPR corrosion sensors implemented in a mock-up bridge cable has been presented. Next step of the project will consist in the deployment of such sensors at two locations on the Manhattan Bridge main cable in New York City.

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